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Adaptive neuro-fuzzy approach for wind turbine power coefficient estimation

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A B S T R A C T

Wind energy has become a large contender of traditional fossil fuel energy, particularly with the successful operation of multi-megawatt sized wind turbines. However, reasonable wind speed is not adequately sustainable everywhere to build an economical wind farm. In wind energy conversion systems, one of the operational problems is the changeability and fluctuation of wind. In most cases, wind speed can vacillate rapidly. Hence, quality of produced energy becomes an important problem in wind energy conversion plants. Several control techniques have been applied to improve the quality of power generated from wind turbines. In this study, the adaptive neuro-fuzzy inference system (ANFIS) is designed and adapted to estimate optimal power coefficient value of the wind turbines. Neural network in ANFIS adjusts parameters of membership function in the fuzzy logic of the fuzzy inference system (FIS). The back propagation learning algorithm is used for training this network. This intelligent controller is implemented using Matlab/Simulink and the performances are investigated. The simulation results presented in this paper show the effectiveness of the developed method.

Contents

1. Introduction

Due to global environmental pollution emergence, trends towards the sustainable energy and green power sources such as wind energy have risen. Wind power generation is an important alternative to relieve global warming problem mainly due to its smaller environmental impact and its renewable characteristic that contribute for a sustainable development. Wind energy is one of the economic renewable sources and a feasible alternative to conventional energy sources.

Wind power installed capability has a rapid growth rate. The common goal of the wind power plants is to maximize favorableness by maximizing energy extraction, and therefore the power output of the wind plants often varies with vacillating winds. Until recently there have been no requirements or market motivators for wind turbines to control their power output [1,9]. Higher wind insight levels have increased the interest for wind turbines to provide additional services that are critical to grid dependability by controlling their power output through power control [2,3]. Development of control solutions is a valuable approach to reduce reduction of operations and maintenance costs of wind turbines [4].

Modern large wind turbines can be classified into three different types, including the constant speed type, variable pitch control type and variable speed type. Variable speed wind turbine power generation system is more superior to others because of its

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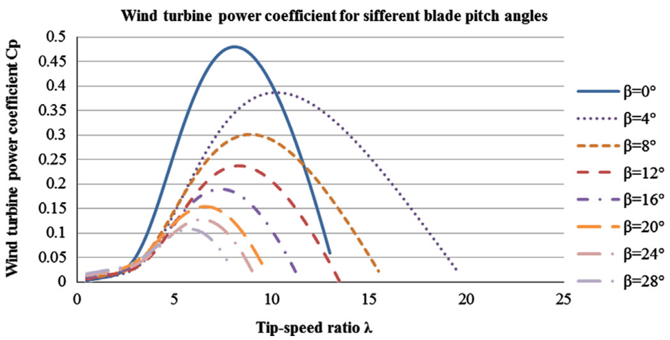

Fig. 1. Wind turbine power coefficient C_p as function of tip-speed ratio λ and blade pitch angle β.

high power extraction efficiency and high power quality [5,6,7]. In the operating wind speed range, in order to achieve the maximum power point tracking of wind turbine, the turbine shaft rotational speed should be adapted optimally with respect to the variable wind speed [8]. Such turbine rotor speed control should base on the real-time information of wind speed. When the wind speed is lower than the rated wind speed, the rotational speed of the wind turbine is controlled according to the variable wind speed by the rotational speed control of the generator for keeping the optimal power coefficient C_p of the wind turbine. The variable pitch control of the wind turbine blade generates the optimal electric power when the wind speed is higher than the rated wind speed.

The wind systems are non-linear power sources that need accurate on-line identification on the optimal operating point [12,13,19]. Also, the power from wind varies depending on the environmental factors such as the fluctuation of wind velocity. Aiming at optimizing such systems to ensure optimal functioning of the unit, new techniques are used today such as the fuzzy logic (FL) [11,14], artificial neural network (ANN) [10,15] and neuro-fuzzy [16–18,20].

Artificial neural networks are flexible modeling tools with capabilities of learning the mathematical mapping between input and output variables of nonlinear systems. One of the most powerful types of neural network system is adaptive neuro-fuzzy inference system (ANFIS) [21]. ANFIS shows very good learning and prediction capabilities, which makes it an efficient tool to deal with encountered uncertainties in any system. ANFIS, as a hybrid intelligent system that enhances the ability to automatically learn and adapt, was used by researchers in various engineering systems [22–28]. So far, there are many studies of the application of ANFIS for estimation and real-time identification of many different systems [29–37].

The key goal of this investigation is to establish an ANFIS for estimation of the wind turbine power coefficient C_p. An attempt is made to retrieve correlation between power coefficient C_p in regard to blade pitch angle and tip-speed ratio of the wind turbine. That system should be able to forecast the power coefficient in regards to the main turbine parameters and wind speed as well.

Fuzzy Inference System (FIS) is the main core of ANFIS. FIS is based on expertise expressed in terms of 'IF–THEN' rules and can thus be employed to predict the behavior of many uncertain systems. FIS advantage is that it does not require knowledge of the underlying physical process as a precondition for its application. Thus ANFIS integrates the fuzzy inference system with a back-propagation learning algorithm of neural network. An ANFIS model will be establish in this study to predict the wind turbine power coefficient in relation to the two main turbine parameters. The experimental training and checking data for the ANFIS network are obtained from analytical analysis of the wind turbine power output.

The basic idea behind the soft computing methodology is to collect input/output data pairs and to learn the proposed network from these data. The ANFIS is one of the methods to organize the fuzzy inference system with given input/output data pairs [38,39]. This technique gives fuzzy logic the capability to adapt the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data [40].

In Section 2, wind turbine conversion power is explained in detail. The main principle of the adaptive neuro-fuzzy inference system (ANFIS) is presented in Section 3. Section 3 also presents the ANFIS model of the wind turbine power estimation. Section 4 summarizes the results and provides the synthesis of measurement data. Finally, Section 5 offers some concluding remarks and future-work directions.

2. Wind turbine power

The major components of a typical wind energy conversion system include a wind turbine, a generator, interconnection apparatus, and control system. Therefore, the design of a wind energy conversion system is complex. The most important part of a wind energy conversion system is the wind turbine transforming the wind kinetic energy into mechanical or electric energy. The system basically comprises a blade, a mechanical part and an electric engine coupled to each other. The kinematical energy of wind is the function of wind speed, the specific mass of air, the area of air space where the wind is captured and the height at which the rotor is placed. The power available in a uniform wind field can as expressed as

$$P_w = \tfrac{1}{2}\rho A v^3 \tag{1}$$

where P_w is the power [W] of the wind with air density ρ [kg/m^3] and wind speed v [m/s] is passing through the swept area A [m^2] of a rotor disk that is perpendicular to the wind flow. The wind turbine can only capture a fraction of the power available from the wind. The ratio of captured power to available power is referred to as the power coefficient

$$C_p = (\beta, \lambda) \tag{2}$$

which is a function of the collective blade pitch angle β and the tip-speed ratio λ. The tip-speed ratio is defined as the ratio of the tangential velocity of the blade tips divided by the effective wind speed, or

$$\lambda = \frac{R\Omega_r}{V_e} \tag{3}$$

where R is the rotor radius, Ω_r is the rotor speed, and V_e is the effective wind speed perpendicular to the rotor plane. The value of C_p can be expressed according to [41] as:

$$C_p(\beta,\lambda) = 0.5176\left(\frac{116}{\frac{1}{\lambda-0.08\beta}-\frac{0.035}{\beta^3+1}} - 0.4\beta - 5\right) e^{\frac{-21}{\frac{1}{\lambda-0.08\beta}-\frac{0.035}{\beta^3+1}}} + 0.0068\lambda \tag{4}$$

A characterization of the power coefficient C_p for the wind turbine used in this study is shown as contour plot in Fig. 1 for different values of blade pitch angle β. It is seen that the optimum or maximum value of power coefficient C_p is achieved with $\beta = 0°$.

3. Adaptive neuro-fuzzy inference system

ANFIS can be used for classification, approximation of highly nonlinear functions, on-line identification in discrete control system and to predict a chaotic time series. ANFIS can serve as a basis for constructing a set of fuzzy 'if–then' rules with appropriate membership function to generate the stipulated input–output pairs.

The membership functions are tuned to the input–output data. ANFIS is about taking an FIS system and tuning it with a back propagation algorithm based on the collection of input–output data. The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions (MFs) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. These intelligent systems combine knowledge, technique and methodologies from various sources. They possess human-like expertise within a specific domain – adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns, and help adaptation to environments. ANFIS is tuned with a back propagation algorithm based on the collection of input–output data.

Here the training data is obtained by analytical expression for the wind turbine power coefficient. One half of the data are used for training while the other half is used for checking and validation of the model. With a proper training scheme and fine filtered data-sets, ANFIS is capable to estimate wind turbine power coefficient quite accurately since it learns from training data. This measurement-free architecture also makes it immediately available for operation once they are trained.

There were six membership functions on each input. In this study bell-shaped membership functions were chosen with maximum equal to 1 and minimum equal to 0. Fuzzy logic toolbox in MATLAB was used for the entire process of training and evaluation of fuzzy inference system. Fig. 2 shows an ANFIS structure for two inputs.

In this work, the first-order Sugeno model [42] with two inputs and fuzzy IF–THEN rules of Takagi and Sugeno′s type [43,44] is used:

$$\text{if } x \text{ is } A \text{ and } y \text{ is } C \text{ then } f_1 = p_1 x + q_1 y + r_1 \tag{5}$$

The first layer consists of input variables membership functions (MFs), input 1 and input 2. This layer just supplies the input values to the next layer. The inputs are blade pitch angle and tip-speed ration of the wind turbine. In the first layer every node is an adaptive node with a node function $O = \mu_{AB}(x)$ and $O = \mu_{CD}(x)$ where $\mu_{AB}(x)$ and $\mu_{CD}(x)$ are MFs. In this study, bell-shaped MFs with maximum equal to 1 and minimum equal to 0 is chosen.

The second layer (membership layer) checks for the weights of each MFs. It receives the input values from the 1st layer and acts as MFs to represent the fuzzy sets of the respective input variables. Every node in the second layer is non-adaptive and this layer multiplies the incoming signals and sends the product out like $w_i = \mu_{AB}(x) * \mu_{CD}(y)$. Each node output represents the firing strenght of a rule.

The third layer is called the rule layer. Each node (each neuron) in this layer performs the pre-condition matching of the fuzzy rules, i.e. they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights which are normalized. The third layer is also non-adaptive and every node calculates the ratio of the rule′s firing strenght to the sum of all rules′ firing strenghts like $w_i^* = (w_i / w_1 + w_2)$, $i = 1, 2$. The outputs of this layer are called normalized firing strenghts.

The fourth layer is called the defuzzification layer and it provides the output values resulting from the inference of rules. Every node in the fourth layer is an adaptive node with node function $O_i^4 = w_i^* x f = w_i^* (p_i x + q_i y + r_i)$ where $\{p_i, q_i, r\}$ is the parameter set and in this layer is referred to as consequent parameters.

The fifth layer is called the output layer which sums up all the inputs coming from the fourth layer and transforms the fuzzy classification results into a crisp (binary). The output represents estimated wind turbine power coefficient. The single node in the fifth layer is not adaptive and this node computes the overall

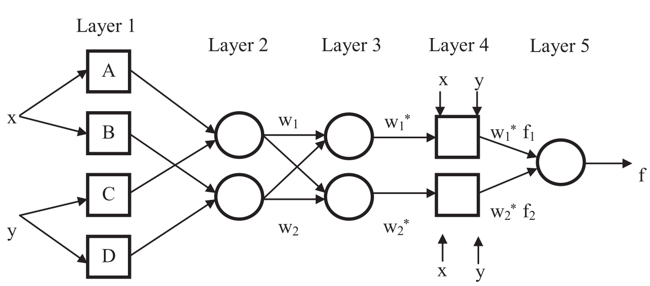

Fig. 2. ANFIS structure.

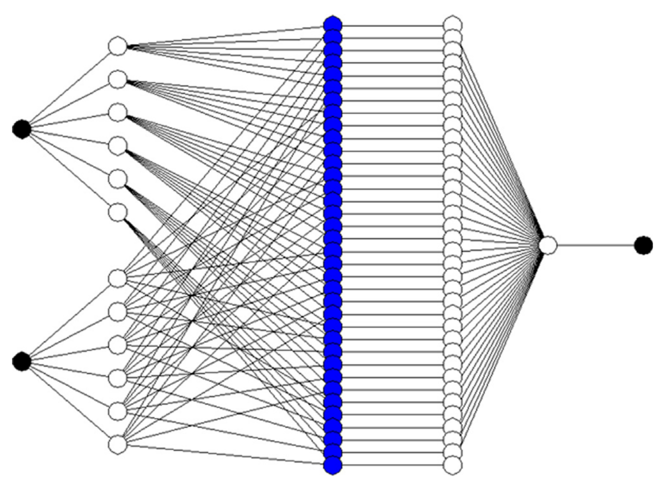

Fig. 4. ANFIS structure.

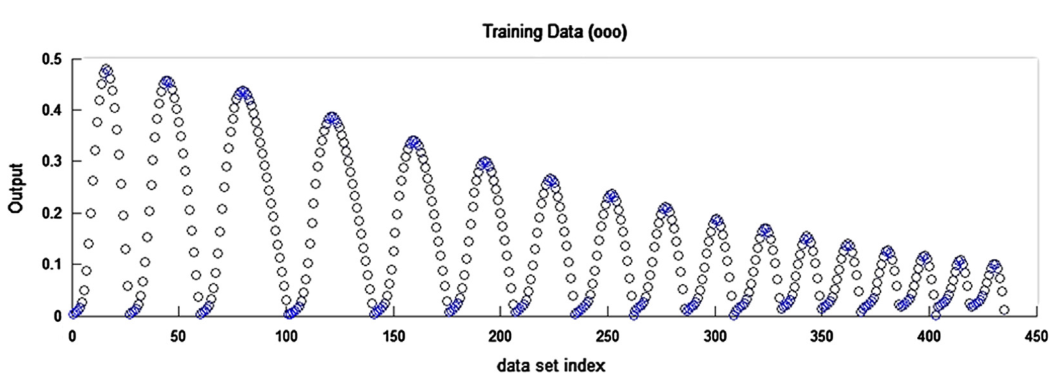

Fig. 3. ANFIS training data.

output as the summation of all incoming signals

$$O_i^4 = \sum_i w_i^* x f = \frac{\sum_i w_i f}{\sum_i w_i} \tag{6}$$

The hybrid learning algorithms were applied to identify the parameters in the ANFIS architectures. In the forward pass of the hybrid learning algorithm, functional signals go forward until layer 4 and the consequent parameters are indentified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent.

4. Results

In this paper ANFIS training and checking data were extracted using analytical expression [4] of the wind turbine power coefficient.

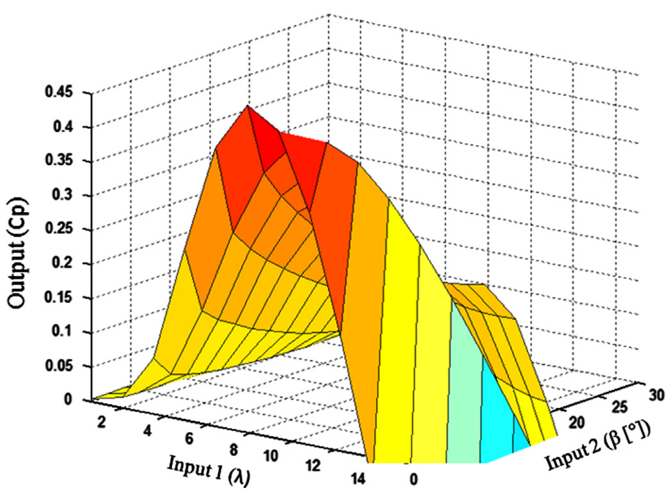

Fig. 5. ANFIS predicted relationship between blade pitch angle, tip-speed ratio and wind turbine power coefficient.

The training data is shown in Fig. 3. The ANFIS network had six bell-shaped membership functions for each input separately.

Minimal training error of the neural network for the used membership functions was 0.0002421. It is not appropriate to further increase the number of the membership functions since there are too many parameters. ANFIS structure for two inputs and six membership functions for each input are shown in Fig. 4. The final decision surface after ANFIS training is shown in Fig. 5.

Fig. 6 shows comparison of the ANFIS predicted results and the experimental training data. Output of the fuzzy inference system is depicted by red stars and the training data is depicted by circles in the Fig. 6. The results show that the ANFIS predicted deviation from the experimental training data was negligible.

The wind turbine power coefficient as function of the blade pitch angle β, rotor radius R, rotor speed Ω_r and effective wind speed V_e is impemented in MATLAB Simulink block diagram as it shown in Fig. 7. For example, for blade pitch angle $\beta = 15°$, rotor radius $R = 75$ m, rotor speed $\Omega_r = 10°/s$ and effective wind speed $V_e = 150\ m/s$ ANFIS estimates the wind turbine power coefficient 0.074. This approach is very usefull for fast estimation of the wind turbine power coefficient according to the main wind turbine parameters and wind speed variation as well.

5. Conclusion

The impact of the variation in the wind speed, blade pitch angle, and rotor tip speed and rotor radius of the wind turbine on the performance of the wind energy system is investigated in the paper. As the parameter for measuring performance of the wind turbine power coefficient C_p was used. A systematic approach to achieving the wind turbine power coefficient by means of ANFIS strategy was investigated. A Simulink model was developed in MATLAB with the ANFIS network for the wind turbine power coefficient estimation. The main advantage of designing the ANFIS coordination scheme is to estimate wind turbine power coefficient as the main turbine parameter according to wind speed, blade

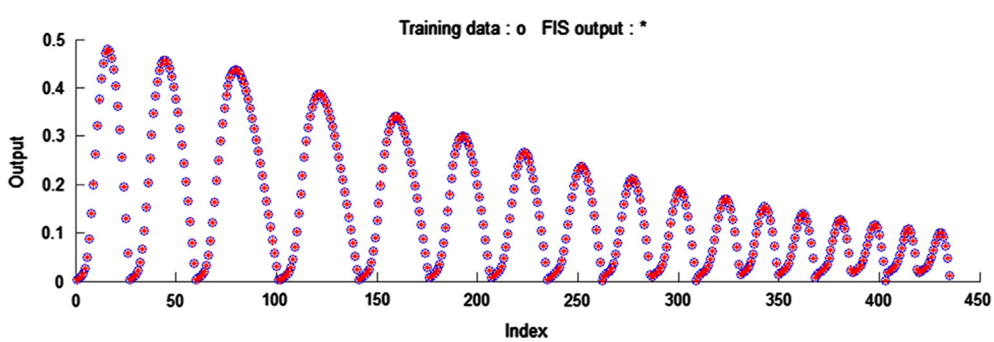

Fig. 6. ANFIS testing.

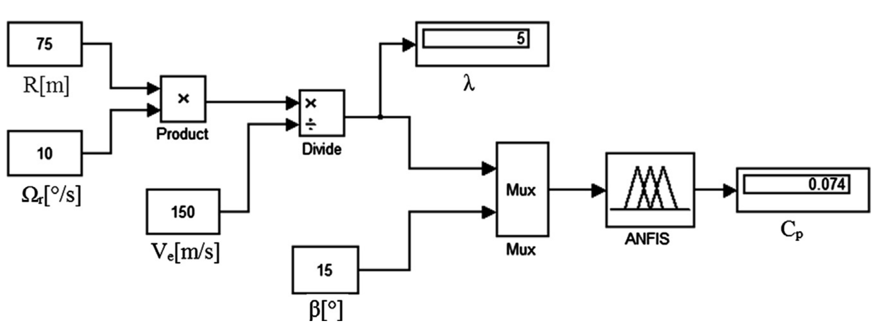

Fig. 7. Simulink block diagram for estimation of wind turbine power coefficient.

pitch angle, and rotor tip speed and rotor radius. Simulations were run in MATLAB and the results were observed on the corresponding output blocks.

The main advantages of the ANFIS scheme are: computationally efficient, well-adaptable with optimization and adaptive techniques. The developed strategy is not only simple, but also reliable and may be easy to implement in real time applications using some interfacing cards like the dSPACE, data acquisition cards, NI cards, etc. for control of various parameters. This can also be combined with expert systems and rough sets for other applications. ANFIS can also be used with systems handling more complex parameters. Another advantage of ANFIS is its speed of operation, which is much faster than in other control strategies; the tedious task of training membership functions is done in ANFIS. One of the most important features of the proposed ANFIS network is identification and estimation of the optimal wind turbine power coefficient.

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